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Computer-Aided Design AND APPLICATIONS

Iterative Optimization of Image Design by Big Data of User Feedback and CAD Implementation

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Abstract. This article delves into the utilization of user feedback big data for iterative refinement of image design, integrating computer-aided design (CAD) technology to streamline the process. Addressing the limitations of conventional approaches, it introduces a big data-driven, user feedback-guided iterative optimization framework for image design. This framework leverages real-time collection and analysis of user feedback to steer the iterative design process. Coupled with CAD software's real-time rendering and preview capabilities, it facilitates swift iteration and fine-tuning of image designs. Experimental evaluations assess the algorithm's proficiency in image feature extraction, Gaussian blur control, and detail reconstruction, contrasting errors across training and test sets. The findings reveal that the proposed method promptly addresses user needs, yields satisfactory image optimization solutions, and reduces overall error by approximately 15% relative to traditional algorithms on the test set. In summary, the integration of user feedback big data with CAD technology for iterative image design optimization notably enhances design quality.

Keywords: User Feedback; Big Data Drive; Image Design; Iterative Optimization; CAD Implementation
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1 INTRODUCTION

Image super-resolution reconstruction technology is a key technology in the field of computer vision, aimed at restoring blurry low-resolution images into high-resolution images containing rich information. It is widely used in many fields, such as object recognition, data transmission, medical imaging, video reconstruction, remote sensing imaging, etc. The traditional network model has weak global capture ability for low-resolution image space and channels and ignores the proportion of local features in the entire mapping process [1]. In the traditional image design process, designers often rely on personal experience, market research, or small-scale user testing to guide design decisions [2]. Although this method can reflect the needs of users to a certain extent, it is difficult to comprehensively and accurately capture the market dynamics and user psychology due to factors such as small sample size and long feedback collection period [3]. Big data analysis can handle massive and heterogeneous user data and provide a scientific basis for design iteration by deeply mining information such as user behavior patterns and emotional tendencies so as to realize precise positioning and personalized customization of design. User's direct feedback, such as comments, scores and clicks, is the direct basis for evaluating the design effect and identifying user's needs. Indirect feedback, such as user behaviour trajectory and social media interaction, can reveal deeper changes in user psychology and preferences. In recent years, with the continuous development of deep learning technology, the use of convolutional neural networks for super-resolution reconstruction of low-resolution images has achieved good results. The strength of convolutional neural networks lies in their multi-layer network structure, which can autonomously learn the deep features of input data, and different levels of networks can learn different levels of features [4]. Most super-resolution reconstruction algorithms based on convolutional neural networks suffer from complex network structures, large model parameter quantities, and high resource consumption. Insufficient utilization of hierarchical information results in texture information and edge structure of the reconstructed image deviating from the true high-resolution image [5]. The resolution of an image directly affects the amount of information it can contain. The higher the resolution, the greater the information it contains, and the more delicate the visual experience it gives people. Therefore, people's requirements for image resolution are becoming increasingly high. Images are a general term for various shapes and images [6]. In today's society, images serve as important carriers of information, the foundation of human vision, a direct reflection of natural scenery and objective matter, and an important source of human understanding of humanity and the world. In order to solve the problem of image blur caused by the limitations of optical equipment and complex natural scenes, image super-resolution reconstruction technology has emerged. However, in practical applications, convolutional neural networks are constrained by various factors [7].

In addition, for the practical application of 3D printing technology, this software has been specially optimized for compatibility with different types of printers, especially for affordable FDM printers. At the same time, the software can capture and analyze user interaction behavior and design preferences in real time, providing data-driven design guidance for designers [8]. This software not only simplifies the conversion process from flat patterns to design patterns and then to 3D printed clothing models but also integrates the analysis mechanism of user feedback big data, making the iterative optimization of clothing design efficient and accurate. This process not only accelerates the design cycle but also ensures that the final product can closely meet market demand and improve user satisfaction [9]. Targeting increases the number of filters and deepens the network layers to capture more feature information in order to achieve better image reconstruction results. At the same time, accurate modelling of information in the feature channel domain and the spatial domain is carried out to generate feature maps containing rich information, enhance the mapping relationship of the network, and finally, gradually aggregate the feature information of different branches to improve feature utilization. Some scholars have proposed a super-resolution reconstruction algorithm based on a multi-channel perception residual module. However, neglecting the influence of different channels and spatial positions on the reconstruction effect leads to insufficient multi-level feature extraction and loss of details in low-resolution images. In the process of image super-resolution reconstruction, the problem of slow network training speed and strict convergence conditions due to the limitations of various module parameters has become increasingly prominent, and each network branch cannot achieve maximum performance [10]. The algorithm uses filters with different receptive fields to perform feature extraction, learning the correlation between channels in different feature layers and multi-scale receptive fields and using the attention mechanism to adaptively adjust the weight ratios of different branches to learn deeper mapping relationships between low-resolution images and high-resolution images, solving the problem of difficulty in learning long-distance information from low-resolution images. Therefore, this article proposes a super-resolution reconstruction algorithm based on adaptive weight adjustment, which uses multiple adaptive modules to form a nonlinear mapping unit. Secondly, mixed residual connections are used between modules to fuse low-frequency and high-frequency information in the model effectively.

Highlights:

(1) In this study, user feedback big data is integrated into the iterative optimization process of image design for the first time, and a set of systematic design iterative strategies is constructed. This strategy considers the direct feedback from users and combines the indirect feedback (such as user behaviour patterns) for comprehensive analysis, which ensures that the direction of design iteration not only meets users' expectations but also leads the market trend.

(2) This research aims to address the shortcomings of traditional CAD systems in handling user feedback and proposes an intelligent upgrade scheme for CAD systems. By integrating a user feedback big data analysis module, the CAD system can automatically analyze user feedback, generate design improvement suggestions, and assist designers in rapid iteration.

This article first expounds on the research background, significance, and research status and then discusses the relevant theoretical basis, the processing and analysis methods of user feedback big data, the specific strategy of iterative optimization of image design, the intelligent upgrade and integration scheme of CAD system, and the feasibility of the system through experiments. Finally, summarize the research results, point out the shortcomings, and look forward to the future research direction.

2 RELATED THEORETICAL

Big data refers to a vast, diverse, and rapidly processed dataset that surpasses the processing capabilities of traditional database tools in terms of capture, storage, management, and analysis. Big data analysis is characterized by 4Vs: volume, speed, diversity, and value, starting from collecting data through sensors, network devices, social media, and other platforms. Preprocessing involves cleaning, denoising, and formatting the collected data to improve its quality. Storage solutions, such as distributed file systems and NoSQL databases, address the storage challenges of big data. The core of big data analysis is technologies such as data mining, machine learning, and statistical analysis, which extract valuable insights from massive datasets. Visualization technology presents analysis results in an intuitive and understandable way, facilitating user understanding and decision-making. User feedback refers to the comments, suggestions, and opinions that users have about a product or service after using it. Rahkar and Ardabili [11] collect and analyze user feedback, allowing businesses to understand user satisfaction and expectations for products timely, and thus improve products in a targeted manner. The analysis methods for user feedback include quantitative analysis and qualitative analysis. In the field of computer vision, image segmentation refers to dividing an image into different regions, aiming to simplify or transform the representation of the image, making its meaning clearer and easier to analyze. On the other hand, the subjective characteristics of human knowledge cognition and visual perception often make the criteria for division not unique or present uncertainty. Wan et al. [12] used fuzzy membership functions to effectively characterize the fuzzy characteristics of pixel membership relationships in images. The fuzzy C-Means (FCM) algorithm is a fuzzy clustering method based on the objective function, which can better characterize the fuzzy characteristics of pixel membership relationships and meet the requirements of unsupervised segmentation. The FCM algorithm transforms the image segmentation problem into solving the optimal solution problem of constrained nonlinear programming. There are many algorithms for image segmentation, but there is no universal method and strategy. Therefore, it has always been regarded as a bottleneck in the field of computer vision, inspiring people to conduct in-depth research. The ambiguity and uncertainty of such concepts cannot be effectively modelled using classical set theory but can be well addressed through fuzzy set theory. This method is designed to be simple, easy to implement, and can effectively segment medical images, making it a popular image segmentation method in recent years. The quality of image segmentation results directly affects the accuracy of object representation and description, as well as feature extraction, which in turn affects the research of pattern recognition and computer vision. Uneven lighting or other external factors make the boundaries of image features blurry and difficult to distinguish clearly. The theoretical method based on fuzzy sets provides a solid theoretical foundation for fuzzy analysis in image segmentation. By minimizing the objective function, the optimal distribution of membership functions is obtained, and pixel partitioning is achieved through deblurring processing.

Through an intuitive interface, Wang et al. [13] carefully examined the processing results of each model on the design image, including correct predictions and incorrect classifications, in order to quickly identify the strengths and weaknesses of the model. DeepCompare not only systematically compares the performance of deep learning models in image design tasks but also intuitively reveals potential mechanisms of model behavior, enabling users to evaluate trade-offs between two or more models interactively. DeepCompare provides the ability to trace test results back to specific neurons, allowing for a deeper understanding of which neurons play a critical role in identifying specific design elements and providing precise guidance for model tuning. Some scholars have designed and implemented a visual analysis tool called DeepCompare. By integrating user feedback data, DeepCompare can help designers accurately locate design defects in each iteration and use insights from deep learning models to guide design adjustments. Finally, through two case studies based on real-world image design tasks, Zhang et al. [14] preliminarily validated the effectiveness of DeepCompare in improving design efficiency, optimizing design quality, and promoting design fairness. Meanwhile, by comparing the performance of different models under the same feedback data, designers can choose or combine models more wisely to balance the relationship between design creativity, technical feasibility, and user satisfaction.

Image segmentation is at the bottom level of image analysis and is often considered an important technique between image processing and image analysis. Zhang [15] obtained high-level image features (such as edges, regions, or shapes) from it, laying the foundation for subsequent object feature extraction and target expression. Therefore, accurate image segmentation provides a guarantee for the development of pattern recognition and computer vision. Image segmentation utilizes the underlying features of an image, such as grayscale, texture colour, coordinates, etc., to divide the image into different regions. The basic idea of a neural network-based image segmentation algorithm is to simulate the human learning process. The entire network is composed of parallel nodes, each of which receives information from multiple higher-level nodes and generates an output. The image segmentation method based on neural networks utilizes feedback network reinforcement learning, which has strong robustness to noise, as well as good fault tolerance and searchability. Neural network methods can be divided into two types: feature-based and pixel-based. Feature-based methods train feature classifiers to extract effective image features for segmentation. The connection relationships and weights between nodes are trained using training samples. After the neural network is trained, the input layer takes in the features of the image, and the output layer obtains the classification results. Due to the large number of node connections, it is easy to consider pixel spatial relationships. Meanwhile, influenced by the imaging principle, when image features are mapped from multidimensional space to one-dimensional space, the resulting pixel features of the image are actually the result of the mutual influence of multiple points. Zhu et al. [16] analyzed medical images as an example. Medical images have a higher grayscale resolution, spatial resolution, fewer colour types, and more pronounced blurriness in image features. This can result in similar features between objects or regions, making the boundaries of different objects or regions uncertain, i.e. ambiguity (the lack of clarity in the extension of concepts or object sets).

3 USER FEEDBACK ON BIG DATA-DRIVEN ITERATIVE OPTIMIZATION OF IMAGE DESIGN

Different interpolation algorithms have significant effects on the colour restoration of images. An excellent interpolation algorithm can accurately estimate the colour of the original image and make the generated SR image more realistic. This article presents an interpolation algorithm based on image segmentation. In this algorithm, the SR image is divided into small blocks with a liquid crystal dot area as a whole, and these irregular segmentation intervals are used as the threshold for selecting adjacent points. In practice, this interpolation algorithm based on reconstruction actually corresponds to linear interpolation twice, thus improving the accuracy and effect of interpolation. For the reconstruction of visual information within the regional digital image, area S' is utilized. In the edge contour portion of the digital image located in the fuzzy region, the feature point x',y' is extracted. Subsequently, texture gradient decomposition is conducted, and the texture distribution set for the digital image in the fuzzy area is calculated as follows:

$$w(i,j) = \frac{1}{Z(i)}\exp\left(-\frac{d(i,j)}{h^2}\right) \tag{1}$$

$Z(i)$ serves as both the first-order and second-order texture distribution operator. Following effective computation, an analysis of visual communication constraints' parameters is feasible. To streamline the calculation, relevant parameters are substituted and transformed as follows:

$$W' = \frac{1}{2}f(x',y',z') + E \tag{2}$$

The formula (x',y',z') denotes the 3D coordinate value subject to visual constraints, while E signifies the data's weighted component. The matching effect can be computed directly via formula transformation.

The iterative reconstruction algorithm is the core of the iterative optimization of image design. Through continuous iteration, the image design can be gradually optimized to make it more in line with the needs of users. The flow of the iterative reconstruction algorithm is shown in Figure 1. When selecting the initial image, this article selects the image with the best visual effect from the low-resolution image as the starting point, and after interpolation and filtering, it is used as the initial estimation of the SR image.

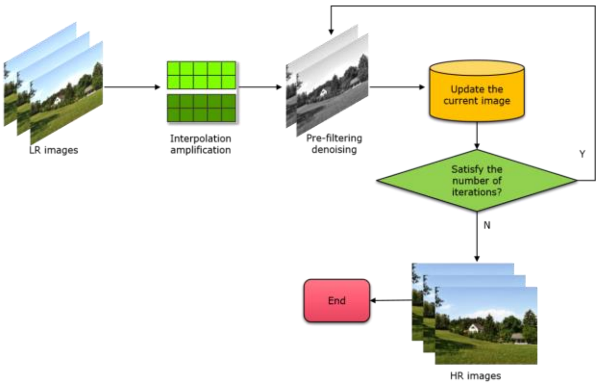


Figure 1: Flow chart of the iterative reconstruction algorithm.

In the iterative process, the optimal solution can be approached step by step by constantly adjusting the design parameters and optimization algorithm. When the difference between the convergent solution and the real solution is a small fixed value, it is considered that an effective solution has been obtained, and the iterative process can be ended at this time.

Both images share the same Fourier amplitude but differ in phase values because of displacement. The phase deviation is given by $e^{j(\theta_1-\theta_2)}$. Specifically, computing the cross-power spectrum of the two images yields a phase equivalent to the phase difference between them.

$$e^{(w_x dx+w_y dy)} = \frac{F_1(w_x,w_y)F_2^*(w_x,w_y)}{\left|F_1(w_x,w_y)F_2^*(w_x,w_y)\right|} \tag{3}$$

By applying the Fourier transform, the cross-power spectrum converts from frequency to spatial domain, resulting in a pulse function. This means that, apart from the displacement location, all other values are nearly zero. The pulse at this displacement indicates the optimal alignment between the images.

The interpolation algorithm Ψ for pixel gray value f can be decomposed into two components: Ψ_1 and Ψ_2, both involving spatial reconstruction.

$$f\ P_{i,j} = \Psi\ E_{i,j} = \Psi_1\ \Psi_2\ E_{i,j} = \Psi_1\ \gamma^{ij} \tag{4}$$

Here γ^{ij} represents the excessive vector.

In γ^{ij}, all values of elements x_n are derived through respective adjacent one-dimensional interpolations.

$$\gamma^{ij} = \left[x_1, x_2, \cdots, x_T\right]^T \tag{5}$$

By doing so, the two-dimensional interpolation issue in the image is converted into a one-dimensional interpolation problem.

Detail reconstruction plays a crucial role in the iterative refinement of image design. It aims to enhance the image's overall visual appeal by refining overlapping zones and intricate details. As illustrated in Figure 2, placing high-resolution tiles in their designated spots and averaging the overlaps suffices. This technique effectively mitigates stitching artifacts and blur, thereby enriching the image's detail rendering.

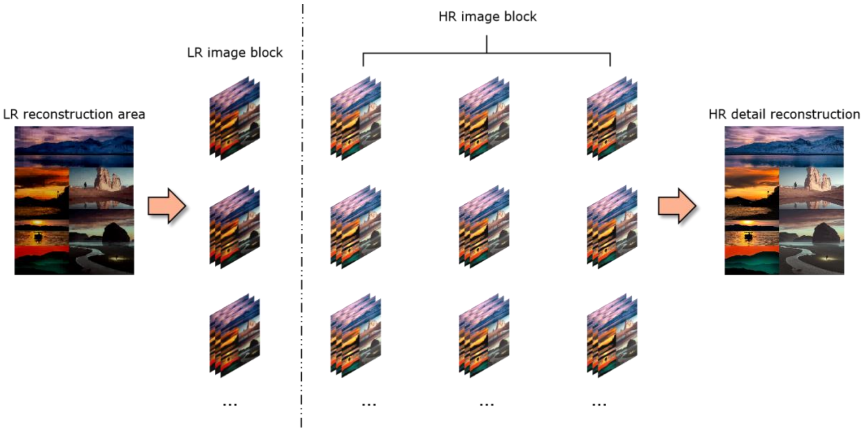


Figure 2: Process of detail reconstruction.

Detail reconstruction can further optimize the visual effect of the image. This includes adjusting parameters such as colour saturation, contrast, and sharpness and adding special effects and filters to enhance the artistic sense and expressive force of the image.

This article's algorithm model yields two outputs: the sparse coding coefficient α_y and the mean value u_i of the low-resolution (LR) input image. However, only α_y is utilized for reconstructing the super-resolution (SR) image block, rendering u_i a hidden variable during optimization. For the LR input image y, based on the maximum posterior probability definition, the maximum posterior probability α,θ is given as follows:

$$\alpha_y, \theta_y = \arg\max_{\alpha,\theta} P\ \alpha, \theta \middle| y \tag{6}$$

According to Bayesian theorem:

$$\alpha_y, \theta_y = \arg\max_{\alpha,\theta} P\left(y \middle| \alpha,\theta\right) \times P\left(\alpha,\theta\right) \tag{7}$$

Here $P\left(y \middle| \alpha,\theta\right), P\left(\alpha,\theta\right)$ signifies the probability and prior terms, respectively.

In the SR image reconstruction algorithm leveraging dual-gallery learning, the gallery's construction method is pivotal. The algorithm's core objective is to capture abundant high-frequency information, which enhances the clarity of the reconstructed image's texture and edges, thereby improving the restoration effect. Upon training the chosen gallery category, it acquires $\left(HFD_{1STi}, LFD_{1STi}\right), i = 1,2,\cdots,k$. The algorithmic process unfolds as follows:

$$\begin{aligned} &\arg\max_{LFD_{1STi},\ a^*} \sum_k \left\| y - LFD_{1STi} a^* \right\|^2 \\ &s.t \quad \left\| a^* \right\|_0 \le L \forall_k \end{aligned} \tag{8}$$

The formula a^* denotes the sparse coefficient y within gallery LFD_{1STi}, y signifies an image block in the LR image, and L is the control parameter.

Utilizing the image acquisition model introduced here, the SR restoration process can be summarized as follows:

$$f(x) \approx f_k(x) = \sum_y \left[g_k(y) - n_k(y)\right] h_k^{BP}\left(m_k'(x) - y\right) \tag{9}$$

Here g_k signifies the LR image of the frame k, $g_k(y)$ representing the gray value of the LR image at the position $y = \left[s,t\right]^T$. f denotes the ideal SR image, while $f(x)$ its gray value at the position $x = \left[u,v\right]^T$. f_k is the SR image derived from solving g_k, and n_k represents the superimposed noise defined on g_k. h_k^{BP} can be regarded as an approximation of the inverse point spread function process. m_k' Signifies the pixel mapping relationship from the SR image f to the LR image g_k.

By continuously collecting and analyzing user feedback data, problems in image design can be found in time. For example, when users give feedback that the colour of the image is dark, the image is brightened by adjusting the colour saturation. When the details of the image fed back by users are not clear enough, the details are highlighted by strengthening sharpness processing.

4 CAD IMPLEMENTATION AND SYSTEM INTEGRATION

4.1 System Integration of Iterative Optimization Process of CAD and Image Design

In order to realize the systematic integration of CAD and image design iterative optimization process, a complete design management system must be built. The system should have the following functions:

(1) Design data management: The system should be able to centrally manage all design data, including image files, design elements, and color matching.

(2) Iterative optimization process management: The system should support the whole process of design iterative optimization, including the creation of the first draft of the design, the collection and analysis of user feedback, design modification and adjustment, etc.

(3) User feedback integration: The system should be able to integrate user feedback data and provide intuitive feedback analysis results for designers.

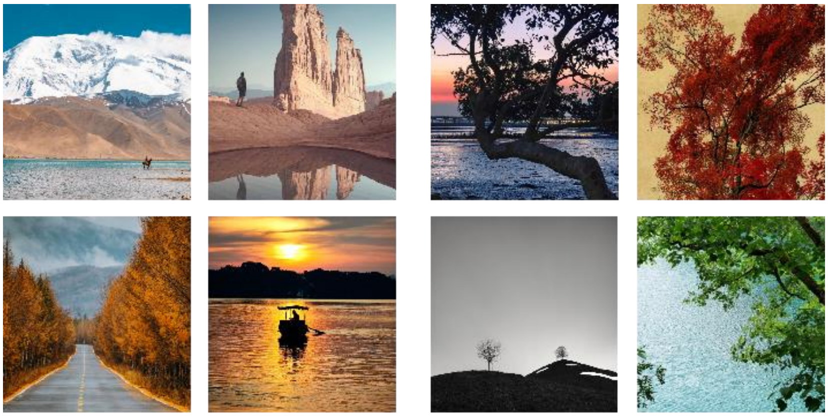
(4) Seamless connection between CAD and iterative optimization system: In order to realize system integration, it is needed to ensure a seamless connection between CAD system and iterative optimization system. This includes data format compatibility, synchronous updating of design elements and real-time transmission of user feedback.

4.2 Key Technologies in System Integration

In the process of realizing the system integration of the iterative optimization process of CAD and image design, several key technologies are involved, Data exchange and sharing technology: In order to ensure data exchange and sharing between the CAD system and iterative optimization system, it is needed to adopt standardized data formats and interfaces. User feedback analysis technology: In order to extract useful information from user feedback, text analysis, emotion analysis and other technical means are needed. These technologies can help designers quickly understand the needs of users. Synchronous updating technology of design elements: In system integration, it is needed to ensure that the modification of design elements in CAD systems can be synchronized to an iterative optimization system in real time. System security and stability guarantee technology: In order to ensure the security and stability of system integration, encryption technology, access control mechanism, and fault-tolerant design are needed.

5 EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

Experimental verification is pivotal in the iterative refinement of image design, ensuring the algorithm's efficacy and practicality. The experiment employs diverse image datasets to evaluate the algorithm's performance comprehensively. Using advanced CAD software, the real design environment is simulated, enabling designers to preview their works in real time and facilitating detailed adjustment. At the same time, combined with a dynamic adjustment strategy, the design flexibility is further improved. Figure 3 shows some samples in the data set, which cover different image styles and types, ensuring the universality and representativeness of the experiment.



(a) Normal sample (b) Negative sample

Figure 3: Partial sample of data set.

Throughout the experiment, we scrutinize the optimal solution's curve to gauge the algorithm's convergence speed and stability. Figure 4 shows the curve of the optimal solution as the number of iterations increases. The whole image feature extraction process is smooth and rapid, and the algorithm can quickly approach the optimal solution.

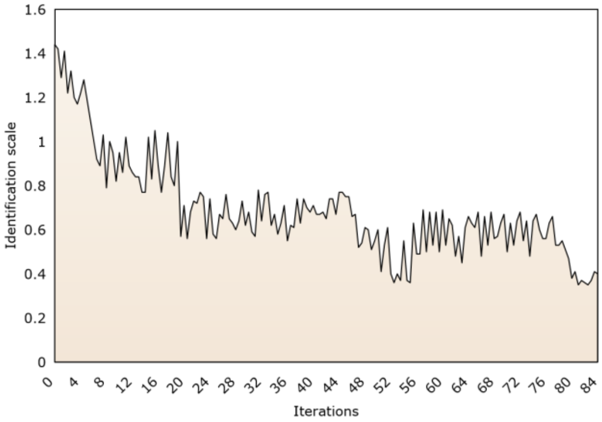


Figure 4: Variation curve of optimal solution.

Figure 5: Original image and Gaussian blur effect under different radii.

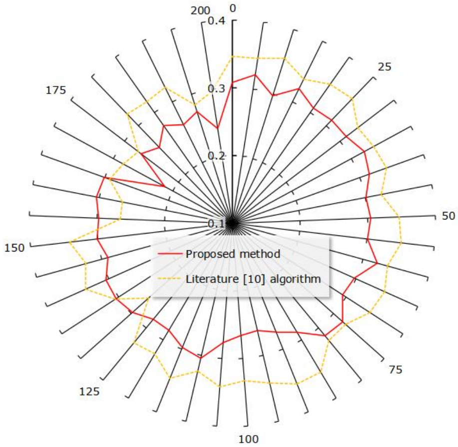


Figure 6: Training set error.

Gaussian blur is a common technique in image processing, which can smooth the details of the image while maintaining the overall structure of the image. Experiments verify the application effect of Gaussian blur in two-dimensional images, and discuss the influence of different Gaussian radii on the degree of blur. As shown in Figure 5, (a) is the original image, (b) and (c) are Gaussian blur effects with radii of 1 and 4, respectively.

When the Gaussian radius increases, the degree of ambiguity also increases; On the contrary, the degree of ambiguity is reduced. Therefore, in practical application, it is very important to choose the appropriate Gaussian radius to achieve the ideal fuzzy effect.

To evaluate the proposed image detail reconstruction algorithm, we compare its performance against the traditional one using both training and test sets. Figure 6 displays the error comparison on the training set, highlighting the proposed algorithm's superior fitting ability with lower errors. Figure 7 presents the test set error comparison, revealing a 15% reduction in error for the proposed algorithm compared to the traditional one.

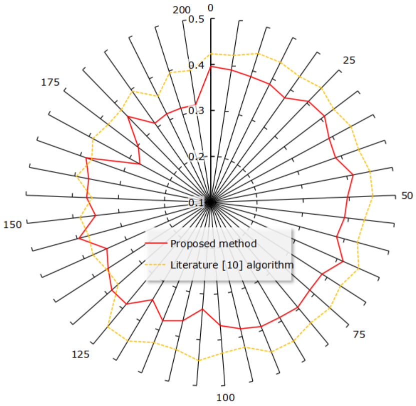


Figure 7: Test set error.

User feedback is an important basis for guiding iterative optimization of image design. Experiments verify the effect of image optimization driven by user feedback big data. As shown in Figure 8, by collecting and analyzing a large number of user feedback data, we can grasp the user's needs more accurately, and thus generate an image optimization strategy that meets the user's expectations.

Figure 8: Comparison of image optimization effects.

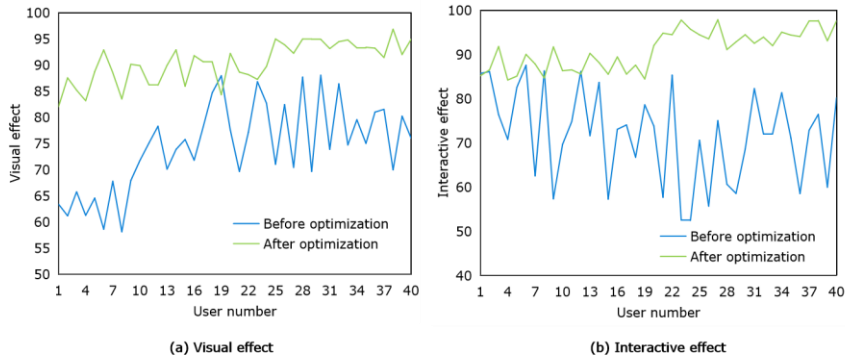


Figure 9: Design scheme score before and after optimization.

In order to further assess the practical application effect of the proposed algorithm, the design schemes before and after optimization are compared. Figure 9 shows the design scheme score before and after optimization. After optimization, the design score is significantly improved. This shows that the proposed algorithm can effectively improve the quality of image design and meet the personalized needs of users.

6 CONCLUSIONS

By building a big data platform for users' feedback, this study has achieved an accurate grasp of users' needs and provided strong data support for iterative optimization of image design. On this basis, combined with the powerful functions of CAD software, the rapid iteration of image design is realized, which significantly improves the design level.

The results show that the proposed algorithm performs well in image feature extraction, Gaussian blur effect control and image detail reconstruction, and can quickly approach the optimal solution and meet the personalized needs of users. Through the user feedback big data-driven optimization strategy, the image optimization scheme that meets the user's expectations is successfully generated, which improves the user's satisfaction.

This method has broad application prospects and can be widely used in advertising design, product design, interior design, and other fields to promote the sustainable development of the image design industry. Future work will continue to study user feedback big data and iterative optimization technology of image design in depth and contribute more to the development of image design.

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REFERENCES

[1] Amura, A.; Aldini, A.; Pagnotta, S.; Salerno, E.; Tonazzini, A.; Triolo, P.: Analysis of diagnostic images of artworks and feature extraction: design of a methodology, Journal of Imaging, 7(3), 2021, 53. https://doi.org/10.3390/jimaging7030053

[2] Aswad, F.-M.; Salman, I.; Mostafa, S.-A.: An optimization of color halftone visual cryptography scheme based on Bat algorithm, Journal of Intelligent Systems, 30(1), 2021, 816-835. https://doi.org/10.1515/jisys-2021-0042

[3] Fan, M.; Li, Y.: The application of computer graphics processing in visual communication design, Journal of Intelligent & Fuzzy Systems, 39(4), 2020, 5183-5191. https://doi.org/10.3233/JIFS-189003

[4] Gutte, V.-S.; Parasar, D.: Sailfish invasive weed optimization algorithm for multiple image sharing in cloud computing, International Journal of Intelligent Systems, 37(7), 2022, 4190-4213. https://doi.org/10.1002/int.22717

[5] Jang, J.; Shin, M.; Lim, S.; Park, J.; Kim, J.; Paik, J.: Intelligent image-based railway inspection system using deep learning-based object detection and weber contrast-based image comparison, Sensors, 19(21), 2019, 4738. https://doi.org/10.3390/s19214738

[6] Kang, M.; Kim, S.: Fabrication of 3D printed garments using flat patterns and motifs, International Journal of Clothing Science and Technology, 31(5), 2019, 653-662. https://doi.org/10.1108/IJCST-02-2019-0019

[7] Li, J.; Yang, J.; Hertzmann, A.; Zhang, J.; Xu, T.: Layoutgan: Synthesizing graphic layouts with vector-wireframe adversarial networks, IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(7), 2020, 2388-2399. https://doi.org/10.1109/TPAMI.2019.2963663

[8] Lu, X.; Chen, Y.; Li, X.: Discrete deep hashing with ranking optimization for image retrieval, IEEE Transactions on Neural Networks and Learning Systems, 31(6), 2019, 2052-2063. https://doi.org/10.1109/TNNLS.2019.2927868

[9] Ma, R.; Mei, H.; Guan, H.; Huang, W.; Zhang, F.; Xin, C.; Chen, W.: Ladv: Deep learning assisted authoring of dashboard visualizations from images and sketches, IEEE Transactions on Visualization and Computer Graphics, 27(9), 2020, 3717-3732. https://doi.org/10.1109/TVCG.2020.2980227

[10] Murugesan, S.; Malik, S.; Du, F.; Koh, E.; Lai, T.-M.: Deepcompare: Visual and interactive comparison of deep learning model performance, IEEE Computer Graphics and Applications, 39(5), 2019, 47-59. https://doi.org/10.1109/MCG.2019.2919033

[11] Rahkar, F.-T.-K.; Ardabili, A.: A hybrid firefly and particle swarm optimization algorithm applied to multilevel image thresholding, Multimedia Systems, 27(1), 2021, 125-142. https://doi.org/10.1007/s00530-020-00716-y

[12] Wan, X.; Wang, C.; Li, S.: The extension of phase correlation to image perspective distortions based on particle swarm optimization, Sensors, 19(14), 2019, 3117. https://doi.org/10.3390/s19143117

[13] Wang, Q.; Chen, Z.; Wang, Y.; Qu, H.: A survey on ML4VIS: Applying machine learning advances to data visualization, IEEE Transactions on Visualization and Computer Graphics, 28(12), 2021, 5134-5153. https://doi.org/10.1109/TVCG.2021.3106142

[14] Zhang, M.; Wang, N.; Li, Y.; Gao, X.: Neural probabilistic graphical model for face sketch synthesis, IEEE Transactions on Neural Networks and Learning Systems, 31(7), 2019, 2623-2637. https://doi.org/10.1109/TNNLS.2019.2933590

[15] Zhang, N.: Application of computer graphics and image software in marine graphic design, Journal of Coastal Research, 106(9), 2020, 600. https://doi.org/10.2112/SI106-136.1

[16] Zhu, M.; Li, J.; Wang, N.; Gao, X.: A deep collaborative framework for face photo–sketch synthesis, IEEE Transactions on Neural Networks and Learning Systems, 30(10), 2019, 3096-3108. https://doi.org/10.1109/TNNLS.2018.2890018